On the Use of Smartphone Sensors for Developing Advanced Driver Assistance Systems

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Abstract. Technological evolution impacts several industries, including automotive. The combination of software with advancements in sensory capabilities results in new Advanced Driver Assistance System (ADAS). The pervasiveness of smartphones and their sensory capabilities makes them an solid platform for the development of ADAS. Our work is motivated by concerns on the reliability of data acquired from such devices for developing ADAS. We performed a number of controlled experiments to understand which factors impact the collection of accelerometer data with smartphones. We conclude that the quality of data acquired is not significantly affected by using different smartphones, car mounts, rates of sampling, or vehicles for the purpose of developing ADAS. Our results indicate that smartphone sensors can be used to develop ADAS.

Keywords: Advanced Driver Assistance Systems · Smartphones · Inertial sensors · Vertical acceleration · Controlled experiments

1 Introduction

Hi-tech features in cars have increased in recent years as a direct result of software-enabled solutions. Advanced Driver Assistance Systems (ADAS), like automatic parking or lane departure warning system, are examples of such advancements resulting from the combination of sensory capabilities and software.

Smartphones are an interesting platform for the development of ADAS, due to their sensory capabilities. However, concerns emerge on the adequacy of these devices when developing ADAS. An assessment on the reliability of data acquired from such devices motivates our work before using their sensors for developing ADAS. There is insufficient knowledge on the extent to which data from smartphones can be used to develop ADAS.

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A considerable number of ADAS rely on inertial data and cameras as the basis for their functionalities. There are inertial sensors embedded in the majority of smartphones available today. In addition, the idea of retrofitting ADAS to existing vehicles fuels some of the smartphone-based ADAS available today.

Obtaining inertial data from these mobile devices is easy. It now becomes relevant to understand which variables impact the quality of data collected. This knowledge is needed to decide to which extent can smartphones support the development of ADAS. Our objective is to clarify which factors may impact the collection of accelerometer data when using a smartphone with the purpose of developing ADAS. We accomplish this by performing controlled experiments where a predefined set of variables are identified and controlled and by analyzing their impact on the quality of sensory data retrieved.

2 State of the Art

ADAS are electronic systems that improve road traffic safety, supporting the driver when driving. Such support ranges from simple information presentation, through advanced assisting, to taking over the driver's tasks in critical situations [6]. A vehicle equipped with an ADAS is referred to as a *smart car*. ADAS aim to provide a fully autonomous vehicle with self-driving capabilities and to guarantee an accident-free driving experience. Most ADAS functionalities exist in independent systems and combining different sensors leads to better decisions, higher system performance, and lower power consumption [14].

Smartphones offer new capabilities, some of them provided by their sensors. With every other person owning one, smartphones can fill in the gap for the vast amount of vehicles without sensory capabilities. This same argument was echoed in research targeting the smartphone as a sensing device for the development of ADAS motivated by the cost of vehicles equipped with sensors [4].

Eriksson et al. produced Pothole Patrol, one of the first road condition monitoring systems, using high-end accelerometer sensors and Global Positioning System (GPS) devices attached to a taxi probe car to collect data [3].

Mohan et al. describe Nericell, a system that uses smartphones to monitor road and traffic conditions [7]. They report experiences as if they were using smartphones to collect acceleration data. However, the description of the implementation reveals the use of special-purpose Sparkfun WiTilt units, which sent acceleration data to the mobile devices for further computation. Other shortcomings in Nericell is the lack of explanations about the selection of thresholds [15], lack of clarification about the labeling technique used [12], and no disclosure of the chosen approach to synchronize data from different devices.

To compare data acquired from multiple sensors, it is crucial to make sure that their readings are synchronized—or, at least, to be conscious of existing skews. As opposed to work previously discussed [3,7], other authors either acknowledged synchronization issues or tried to mitigate them in diverse ways.

Examples include manually shifting labels [13], combining interpolation and shifting of data, and using devices with real-time operating systems [2].

A distinct approach is to use statistical methods to compute data read from different sensors and prepare it for feature extraction. Linear [3,4] or polynomial interpolation [8], and moving average [12,15] are common techniques.

A contrasting method is Dynamic Time Warping (DTW), which provides the possibility to align two time series even if they are out of phase [9]. It achieves an optimal solution in quadratic time and space complexity. This is impractical for dealing with large volumes of data, with memory requirements in the order of a tebibyte (TiB) to handle time series of ∼100 000 measurements [10]. FastDTW [10] solves this difficulty by providing a DTW algorithm with linear time and space complexity, while ensuring a nearly optimal solution.

3 Experiment Planning

During experiment planning, we focused on meeting expectations set by our objectives. A reasonable effort to mimic real world usage was carried out to ensure that knowledge drawn could be used for practical products. Major constraints were identified to prevent them from becoming a risk to the experiments' validity.

The experiments occurred on roads of Braga around Bosch plant and around University of Minho Campus.

3.1 Hypothesis Formulation

Following are the hypotheses tested during our controlled experiments. For each identified variable, a null and an alternative hypothesis was established.

Smartphones—and the inertial sensors embedded within—are very diverse, be it in size, materials, or software version. We anticipated that such differences could have an impact on acceleration values reported by those devices.

Hypothesis $\mathbf{1_0}$: *Using different smartphone models to record accelerometer data does not yield similar measurements of vertical acceleration.*
Hypothesis $\mathbf{1_1}$: *Using different smartphone models to record accelerometer data yields similar measurements of vertical acceleration.*

The car mount holding the smartphone affects the acceleration sensed by it, since the car mount acts as a proxy between the device and the vehicle.
Hypothesis $\mathbf{2_0}$: *Using different car mounts to hold the smartphone does not yield similar measurements of vertical acceleration by a smartphone.*
Hypothesis $\mathbf{2_1}$: *Using different car mounts to hold the smartphone yields similar measurements of vertical acceleration by a smartphone.*

Other authors have demonstrated the importance of the sampling rate on the quality of information collected [5,12], so we studied the result of varying it.
Hypothesis $\mathbf{3_0}$: *Setting different sample rates to acquire the data does not yield similar measurements of vertical acceleration by a smartphone.*
Hypothesis $\mathbf{3_1}$: *Setting different sample rates to acquire the data yields similar measurements of vertical acceleration by a smartphone.*

Vehicles might have influence on the acceleration. Differences in the levels of comfort experienced during a trip in different vehicle models were a good indicator of this effect.

Hypothesis 4_0: *Using different vehicles to travel along the same itinerary does not yield similar measurements of vertical acceleration by a smartphone.*

Hypothesis 4_1: *Using different vehicles to travel along the same itinerary yields similar measurements of vertical acceleration by a smartphone.*

3.2 Variables and Subjects Selection

Both the dependent and independent variables emerged from the examination of our formulated hypotheses. We selected two subjects for each independent variable, with one of them being used in the standard setup. We also identified extraneous variables and assessed their impact on the experiment.

Dependent Variable – Vertical Acceleration: Accelerometer data from each device was collected in $\mathrm{m\,s^{-2}}$. With the geographical globe as referential, the vertical acceleration axis points towards the sky and is perpendicular to the ground plane. To collect acceleration data, one axis of the smartphone was aligned with the vertical acceleration axis.

Independent Variable – Smartphone (Inertial Sensor): We performed experiments with two smartphones from different manufacturers. They were from two different price categories to amplify differences in the quality of their components. Three Nexus 5X were used in this study. This model is fabricated by LG since 2015 and incorporates a BMI160, an inertial measurement unit (IMU) manufactured by Bosch. This was the device used in the standard setup. A Samsung Galaxy S Duos, released in 2012, was also used in the experiments. Its accelerometer data is provided by an MPU-6000, an IMU from Invensense.

Independent Variable – Car Mount: Two iOttie Easy One Touch 3 were used to hold the smartphones during the experiments. This model was chosen for the standard setup because empirical evidence has shown it to be very stable. An unbranded car mount was used to contrast. Empirical evidence demonstrated this unbranded car mount to be very unstable, wobbling a lot even when traveling on itineraries with good pavement conditions.

Independent Variable – Rate of Sampling: The choice of sampling rate for the standard setup was quite pragmatic. Both chosen smartphones reported being capable of sampling data at no more than 200 Hz, so that value was selected. A study regarding road roughness condition proposed the frequency range of 40 Hz to 50 Hz as the best solution to sample smartphone acceleration sensors [1]. Supported in it, the rate of 50 Hz (period of 20 ms) was used to compare.

Table 1 summarizes how the chosen rates of sampling compare to related studies. The standard rate (200 Hz) falls short only to systems where special purpose accelerometers were used. The alternative rate (50 Hz) is in line with other smartphone-based systems.

Table 1. Distance between consecutive accelerometer measurements at different speeds for different systems.

System	Rate (Hz)	Distance (cm) traveling at		
		$25\,\mathrm{km\,h^{-1}}$	$50\,\mathrm{km\,h^{-1}}$	$75\,\mathrm{km\,h^{-1}}$
P^2 [3]	380	1.8	3.7	5.5
Nericell [7]	310	2.2	4.5	6.7
RoADS [12]	93	7.5	14.9	22.4
Tai [13]	25	27.8	55.6	83.3
Our std. setup	200	3.5	6.9	10.4
Our alt. setup	50	13.9	27.8	41.7

Independent Variable – Vehicle: We tried to conduct experiments with two cars representative of the vehicles in operation and having a significant difference in their price points and age. The first car was a Mazda 3 from 2007, chosen for the standard setup since it was always available to us. The second was a Volkswagen Polo from 2016, a rented car available during a single day.

Other Variables: Each experiment testing a hypothesis varied just one of the described independent variables. The influence of a vehicle's speed on information sensed by an accelerometer has been demonstrated [1,2,4,15]. Because of this, speed was categorized as an extraneous variable. Ideally, the speed of vehicles used in the experiments should have been constant during the entire trip, making it a controlled variable. To minimize its impact on the dependent variable, the driver tried to maintain the vehicles' speed at 30km h^-1. Traveling at such speed would mean that collected acceleration data could later be analyzed to identify road anomalies as small as 4.2 cm (see Table 1).

3.3 Experiment Design

During each experiment, a vehicle performed a set of maneuvers on a predefined itinerary to capture data within a city environment. This vehicle was equipped with Android smartphones, each running an app created for this purpose. Car mounts kept the smartphones stable. The Android app had capabilities to acquire, present, and export sensors data from the smartphone. This application collected data from the accelerometer, gyroscope, GPS coordinates, and speed. To annotate the experiment, a co-driver used a second Android application, capable of storing the type of anomaly detected and a timestamp of its occurrence.

Each experiment tested one hypothesis using two setup configurations. One configuration remained the same (same smartphone, car mount, rate of sampling, and car) across every experiment, acting as a control setup. The alternative setup changed only one variable. Every experiment was performed five times.

To ensure a rich diversity of pavement anomalies to be detected on the experiments, we surveyed potential itineraries in Braga. To identify these itineraries, we considered the number of pavement anomalies, the types of anomalies, the itinerary's size, and the possibility to make a full travel with the same speed.

Collection Process Definition: Experimental data was collected by a team of 3 researchers and were performed during periods less prone to traffic congestion. Every repetition of an experiment started with the vehicle stopped but having its engine running for 5 seconds to record accelerometer data, collecting reference values that represent noise caused by the engine. Those values were used to calibrate the smartphone accelerometers. Upon completion of this phase, the Android app started collecting and storing sensors data. The researcher in the co-driver position used the annotations application to mark the start of a recording session and commanded the driver to start moving the vehicle.

While the vehicle was moving, the co-driver made annotations of the pre-determined pavement anomalies as they were experienced. The driver drove through the road without avoiding the anomalies, keeping a constant speed. Reaching the finishing position, the driver stopped the vehicle. After that, the co-driver used the annotations application to label the end of the session and the sensors data application to stop collecting data. Finally, if there were more repetitions of the experiment to perform, the team of researchers moved to the starting point of the itinerary to restart the procedure here described.

Analysis Techniques: A suitable method to test the hypotheses formulated on Sect. 3.1 is to compute the sample correlation coefficient between vertical acceleration collected by the pair of smartphones used in each experiment. This coefficient determines the similarity of reported accelerometer data from distinct devices and how strong that similarity is. It yields a normalized result between -1 (inversely correlated) and 1 (perfectly correlated), with 0 meaning entirely uncorrelated.

Difficulties were anticipated in using this technique. For instance, correlation between raw data is expected to be low due to the noise associated with measurements provided by IMUs embedded in smartphones. Also, since Android is not a real-time operating system (OS), it is difficult to ensure that two different measurements happened at the same time. Lastly, an equal number of data points for both time series is an imperative to compute the correlation between the analyzed datasets.

DTW aims to solve the problem of data sets having different lengths and being out-of-sync, while also reasonably dealing with noise. Given the tendency of DTW to bias the correlation for higher values, a randomization significance test was performed instead of a parametric significance test.

Instrumentation: To assist the operation during experiment execution and data analysis, three special-purpose tools were identified as in need. Smartphones required an Android application to collect and export their sensors data. After testing existing applications with similar features we found that none satisfied our requirements, so we developed a new one—*Bumpr*.

A second smartphone application was needed to assist the researcher's job of annotating recording sessions. With the number of features being rather low, the development of this application—*TapEvents*—was focused on non-functional requirements, namely, on building an efficient user interface that could be used while navigating through the itinerary.

To automate data analysis, a desktop application (1) computes the correlation coefficients of vertical acceleration and (2) statistically validates the results. This application, *TimeWarper*, uses FastDTW [10], an open implementation of the DTW algorithm, to prepare the streams of sensors data for analysis.

4 Experiment Execution

Field experiments took three months, after the procedure described in Sect. 3.3. We present details about each *run*, which refers to an instance of a field study where an experiment is being conducted. A *session* is the time window delimited by the start and end of a driving exercise, during which sensors data is being recorded. Each run aggregates a number of sessions.

4.1 First Run

The first run was carried out and data gathered from this experiment acted as a control group, setting the baseline against which future runs were compared.

A configuration (similar to configuration in Fig. 1) was prepared to accomplish this objective: two Nexus 5X, incorporating each a Bosch BMI160 accelerometer, running the same OS version, with the same recording application version sampling at 200 Hz, mounted on similar iOttie Easy One Touch 3 in identical positions and angles, and inside a single 2007 Mazda 3.

Data from early recording sessions was discarded as they were considered as being part of a warm-up stage. A couple of middle sessions were also disregarded for various reasons, e.g., trucks blocking sections of road. The first run was deemed as concluded after successfully finishing five sessions.

4.2 Second and Third Runs

In order to save time and other resources, the hardware configuration was adjusted so multiple field studies could take place at the same time (see Fig. 1).

The second run scrutinized data coming from two different smartphones with different sensors. A Nexus 5X and a Samsung Galaxy S Duos were part of the hardware configuration. These smartphones encase a Bosch BMI160 and an Invensense MPU-6000, respectively, to measure acceleration.

In the third run, two different car mounts were tested. One of them was an iOttie Easy One Touch 3 and the other was an unbranded equipment, holding the mobile devices in identical positions and angles.

(a) One annotation and three recording applications running on multiple devices

(b) Combining three smartphones and three car mounts allowed to concurrently execute two experiments

Fig. 1. Equipment setup for second and third runs

(a) Both cars in preparation for the experiment

(b) Second car tailgating the first. Photo taken during warm-up session

Fig. 2. Vehicles and setups used to perform the fourth and fifth runs

4.3 Fourth and Fifth Runs

On January 13$^{\text{th}}$, 2017, the fourth and the fifth runs occurred, testing different sample rates and different cars, respectively. Once again, equipment was selected in such way to support running two experiments in parallel (see Fig. 2).

For the fourth run, two different sampling rates data were studied: 200 Hz and 50 Hz (data read each 5 ms and 20 ms, respectively). Lastly, the fifth run probed two different vehicles, a 2007 Mazda 3 and a 2016 Volkswagen Polo. Like in previous runs, all of the other setup parts were kept unchanged.

Performing both runs at the same time had different implications for these two field studies. For example, the Polo was a rented car and had no permission to travel inside University of Minho's campus. Thus, the course had to be adjusted and the portion inside the Campus of Gualtar was switched for a different path with similar length and an approximate number and diversity of anomalies.

Another issue with making an experiment with two different cars was the impossibility of traveling the road in the same exact positions, or even at the same speeds. To address these issues, the driver of the vehicle in the rear tried to keep a constant distance to the one in front of it (see Fig. 2b). We chose a car with cruise control and teams in both cars communicated via a phone call.

5 Data Analysis

We used descriptive statistics to study the central tendency and dispersion of the acceleration. In addition to the number of accelerometer observations (samples), we computed mean ($\bar{x}$), median ($\tilde{x}$), mode, minimum (min), maximum (max), and standard deviation (σ). Table 2 shows data from the first run, with each horizontal band grouping a successful session, and each of the rows in a band regarding one of the two similar Nexus 5X used. So, both setups A and B had similar configurations: the one used as the control group (see Sect. 4.1).

From these tables,[1] we confirmed that most acceleration data points were clustered around 0, with a standard deviation of about $1\,\mathrm{m\,s^{-2}}$. This fell in line with our expectations, as usually a vehicle does not accelerate in the vertical axis, apart from those brief moments when a road anomaly comes across.

The median value was consistently close to the mean, indicating that values were fairly distributed on each side of the average value. It also signals there being no outliers skewing the dataset—or, at least, that such outliers exist with approximately equal frequency on both sides of the median.

Despite the relatively small standard deviation, minimum and maximum values were quite afar from the central points, yielding a high range. We confirmed that points with values so farther apart were associated with the annotated road anomalies which provoked spikes in the monitored acceleration. Despite looking like outliers, these data points increase signal-to-noise ratio (SNR) in the datasets and were not discarded.

5.1 Data Set Reduction

We considered data recorded before (and after) the vehicle initiated (and finished) the trips as noise. To improve the SNR of the datasets, we clipped sensors data prior to (and after) the start (and end) of all sessions using the timestamps collected with the annotations application.

When analyzing Table 2, we detected incorrect data in the first session, with one of the smartphones reporting a very small number of observations (see highlighted row). We confirmed that such data was missing and could not be recovered, so first run's first session was treated as invalid.

5.2 Hypothesis Testing

We tested the hypotheses formulated in Sect. 3.1 with the techniques presented in Sect. 3.3. To assist in this effort, we designed and implemented a software tool, TimeWarper (see Sect. 3.3). Data collected in the control experiment set the baseline correlation coefficient against which the other coefficients were compared. Those comparisons allowed to decide about the proposed hypotheses.

Table 3 shows the computed coefficients for all valid sessions on every run, along with the mean value ($\bar{x}$). We use the mean values to illustrate arguments

[1] Due to space constraints, only first run's table is shown. For all tables, see [11].

Table 2. Descriptive statistics for acceleration data from the first run. Each horizontal band groups a successful session. Highlighted row shows incorrect data found during analysis (see Sect. 5.1). All data from first session was treated as invalid.

Setup	samples	$\bar{x}$ (m s^{-2})	$\tilde{x}$	mode	min	max	σ
A	66 079	−0.020	−0.018	0.035	−13.255	8.758	1.051
B	3047	0.008	−0.019	−0.010	−0.393	0.388	0.146
A	65 078	−0.031	−0.032	0.009	−16.833	9.010	1.064
B	65 234	−0.021	−0.027	0.047	−19.159	15.892	1.163
A	67 326	−0.021	−0.019	0.065	−16.655	8.721	1.046
B	67 322	−0.001	−0.017	0.120	−21.392	15.189	1.098
A	65 928	−0.029	−0.022	0.045	−19.230	9.884	1.042
B	65 648	−0.012	−0.032	−0.080	−23.336	16.941	1.108
A	66 384	−0.034	−0.034	−0.055	−18.669	10.797	1.041
B	66 386	−0.029	−0.042	−0.075	−21.990	15.600	1.109

in this section, but every individual coefficient was statistically validated. As discussed before, the first session of the first run was treated as invalid, so the mean value for the first run was computed over the remaining four valid values.

We expected the correlation coefficient to be high for two similar collection setups sensing the vertical acceleration during a recording session. The control experiment tested this expectation. Running the valid sessions of the first run through TimeWarper yielded a mean correlation coefficient of 0.892, a strong positive correlation (see Table 3).

To test the statistical significance of this result, we processed each valid session using the following technique. Let us start by assuming that the result has no significance. If so, it follows that computing the correlation of data with nothing but noise would produce similar correlation coefficients.

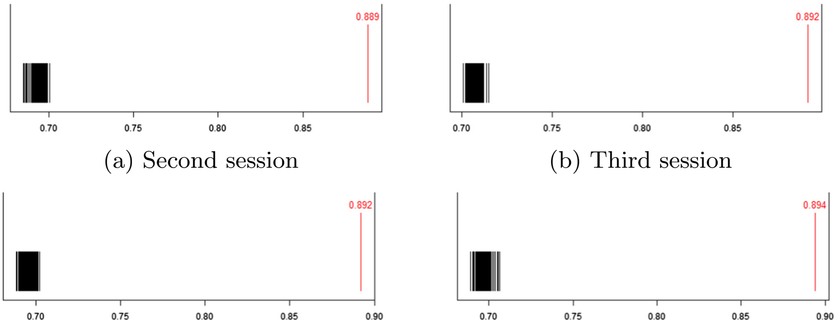
One can produce "noised" versions of the same data by rearranging the order of their data points. Using a Random Shuffle algorithm, 100 randomized copies of each smartphone's acceleration data were produced—the surrogates. Then, each pair of surrogates was warped and its correlation coefficient computed. Lastly, the coefficients were ordered.

The original assumption can be rejected if the correlation coefficient for the original pair, r_0, is at the tails of the coefficients distribution. For a significance level of $\alpha = 0.05$, if the rank of r_0 in the ordered list of coefficients is less than 3 or is greater than 98, then we reject the assumption and consider the result as statistically significant.

Figure 3 plots the ordered lists of coefficients for the first run. For all the graphs for each session from every run, see [11]. For all sessions, the original correlation appeared at the tail of the list, ranking at the 101st position which is

Table 3. Correlation coefficients by run and session. Highlighted cell shows a session for which it was not possible to compute the correlation coefficient due to invalid data. It corresponds to the highlighted row in Table 2.

Session	Run				
	1st (baseline)	2nd (smartphone)	3rd (car mount)	4th (samp. rate)	5th (car)
1	—	0.834	0.845	0.841	0.826
2	0.889	0.828	0.843	0.831	0.835
3	0.892	0.826	0.855	0.836	0.822
4	0.892	0.831	0.852	0.829	0.825
5	0.894	0.830	0.846	0.833	0.825
$\bar{x}$	0.892	0.830	0.848	0.834	0.827



(a) Second session (b) Third session

(c) Fourth session (d) Fifth session

Fig. 3. Correlation coefficients for the first run, including surrogate and original pairs (highlighted). First session's data was rejected (see Sect. 5.1)

greater than required. The initial result of 0.892 was thus considered valid and used as baseline for the experiments analyzed below.

Contrasting with the control experiment, we expected that changing the independent variables would yield smaller correlation coefficients than the baseline. However, we did not have an intuition for the magnitude of the difference.

To test hypotheses 1_0, 2_0, 3_0, and 4_0, we fed into TimeWarper data from the second, third, fourth, and fifth runs, resulting in mean correlation coefficients of, respectively, 0.830, 0.848, 0.834, and 0.827 (see Table 3).

We performed statistical significance tests following the same technique as before. For every session from every run, the original coefficient ranked at 101st, validating each result. Those coefficients have shown strong positive correlations between measurements of vertical acceleration when using different smartphones, car mounts, sampling rates, and vehicles. The results refuted all proposed null hypothesis, implying a value of truth for all alternative hypothesis.

6 Conclusions

Our main contribution is an experimental study on the impact in quality of data collected by different smartphones, car mounts, rates of sampling, or vehicles when developing ADAS. This study shows that the quality of data acquired with smartphone sensors is not significantly affected by using different variations of those elements. It is thus feasible to use smartphone sensors to prototype and develop ADAS without the need to standardize the components used.

Additional studies can be conducted for any of the independent variables to strengthen the confidence on our results. Such studies should both have a greater number of repetitions and study a wider variety of subjects, e.g., by testing different types of vehicles. In particular, it would be interesting to see a further investigation on the car mounts, as their higher mean correlation coefficient seems to be counter-intuitive. A comparison of the capabilities of smartphones versus those provided by special-purpose sensor boxes could also be made. A study focused on vehicles' speed as an independent variable would be very valuable. To do so, a test track and cruise control-equipped cars should suffice.

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